Pulse coupled neural networks with adaptive synapses for image segmentation

Jörg Schreiter, Ulrich Ramacher, Arne Heittmann, Daniel Matolin, and René Schüffny

schreite@iee.et.tu-dresden.de, Arne.Heittmann@infineon.com

Abstract: A network of integrate-and-fire neurons with reciprocal synaptic connections to the four next neighbors is considered. The input to each neuron is the feature of an image, i.e. light intensity. Like in the biological archetype synchronization shall be used as an indicator if the input in certain neurons are related or not. Two rules for the unsupervised adaption of the synaptic weigths have been derived to achieve segmentation image of areas belonging to the same feature.

1 Introduction

To some extend biological neural networks are considered to mark a yet unreached level of signal processing. Therefore there is a strong interest to understand their function, and to resemble some of their features in technical installations. Certain aspects of signal processing in biological neural networks caught our attention: Almost all real neurons use pulse coded information transmission, accordingly they are pulse emitting neurons. Synchronization occurs between neurons signaling connected pieces of information [BGSE01, vdM81, RLS98] A lot of connections are made by adaptive synapses, where adaptivity is either a part of the information processing or acts as a means to adjust connections in systems with unsupervised learning.

One area of interest for applications is object recognition in image processing. To utilize the above mentioned features would mean to use pulse coded image information, and to arrange a pulse coupled neural network such that synchronization of neural activity corresponds to parts of the image which are connected by one or more of their properties. For the ease of implementation we choose a simple image feature as input, such as intensity at a pixel, aka grey scale.

In the following section the integrate-and-fire model is briefly reviewed. Section three explaines how synchronization can be achieved with the help of adaptive synapses. The paper concludes with some details of a massive parallel analog implementation of a pulse coupled neural network (PCNN).

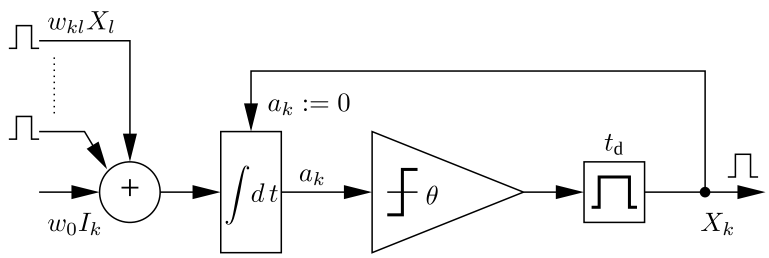

Figure 1: Model of the simple integrate-and-fire (IAF) neuron. Continuous input I_k is weighted by w_0. Together with weighted input pulses from other neurons $w_{kl}X_l$ it is integrated to the membrane potential a_k. When the threshold θ is reached, a_k is reset and an output pulse of fixed duration t_d appears at the pulse output X_k of the neuron.

2 Neural Model

The integrate-and-fire model is quite popular among neural research groups [In00, CBD+03, SMJK98]. The leakage common to most flavors of the model we neglect in the following. Thus, we arrive at the non-leaky integrate-and-fire (IAF) neuron model (although practical analog implementations show some leakage). Let us denote one such neuron by k. Its state is described by a two-state discrete variable $X_k \in \{0, 1\}$ and a continuous state value, the membrane potential $a_k \in \mathbb{R}$. Figure 1 shows the signal flow in the neuron. Each neuron receives a continuous scalar input $I_k \geq 0$ from the input image, and pulsed inputs X_l ($l \in \mathbb{N}\backslash k$) from other neurons. All inputs are weighted by corresponding synaptic weights: w_0 for the continuous input and w_{kl} for a pulsed input from neuron l.

In the receiving state the output X_k of neuron k is equal to zero and the weighted input signals are integrated onto the membrane potential a_k. At a time $t_k^{(\nu)}$ the membrane potential a_k reaches the fixed threshold θ and the neuron switches to the sending state and generates an output pulse. The output X_k is equal to one in the sending state and the membrane potential has no meaning. The neuron stays in this state for a fixed duration t_d (the pulse width). When the pulse is completed the neuron resets the membrane potential a_k and toggles its state again. By this behavior the neuron outputs a pulse or spike of constant duration and amplitude. The beginning of the sending state denoted by $t_k^{(\nu)}$ is referred to as the firing time of the νth pulse of this neuron. The membrane potential in the receiving state can be expressed by

$$a_k(t) = \int_{t_k^{(\nu)}}^{t} \left[\sum_{l \in N_k} w_{kl}(t) \cdot X_l(t) + w_0 \cdot I_k \right] dt \tag{1}$$

with

$$0 \leq a_k(t) < \theta. \tag{2}$$

The next fire event is given by

$$a_k(t_k^{(\nu+1)}) = \theta. \tag{3}$$

Because of the (weighted) continuous input $w_0 I_k$ the neuron repeatedly emits pulses. With a constant input and in the absence of additional pulsed input the pulses occur regularly at a frequency, which is referred to as the free-running frequency:

$$f_{\mathrm{f}} = \frac{w_0 I_k}{\theta + w_0 I_k t_{\mathrm{d}}}. \tag{4}$$

Without loss of generality units for time and membrane potential can be chosen, such that

$$t_{\mathrm{d}} = 1 \tag{5}$$

and

$$\theta = 1. \tag{6}$$

Then, (4) is of the form

$$f = \frac{x}{1+x}. \tag{7}$$

A frequency of 1 in these units would mean one pulse every t_{d}, i.e. without gaps between pulses. That is the asymptotic maximum frequency for arbitrarily large input $w_0 I_k \to \infty$. Figure 2 shows the free-running frequency dependent on input. In our simulation experiments and in the analog implementation we use inputs in the range

$$0 \leq w_0 I_k \leq \frac{\theta}{10\, t_{\mathrm{d}}}. \tag{8}$$

3 Synchronization with Adaptive Synapses

3.1 Adaptation Rules

When two non-leaky IAF neurons k and l are connected reciprocally by two weights w_{lk} and w_{kl}, their pulse rates become interdependent. They will spike synchronously, i.e. with the same frequency f_c and a fixed phase relation, if the weights are adjusted, that it holds:

$$T_{\mathrm{i}} w_0 I_k + T_{\mathrm{p}} w_{kl} = \theta = T_{\mathrm{i}} w_0 I_l + T_{\mathrm{p}} w_{lk}. \tag{9}$$

$T_{\mathrm{i}} = 1/f_c - t_{\mathrm{d}}$ is the non-pulse part of the common period, and T_{p} is the non-overlapping part of the pulses, which is equal for both neurons.

In our network the synchronous activity shall mark neurons and corresponding pixels, which belong to the same segment. Segments are defined roughly by the property that

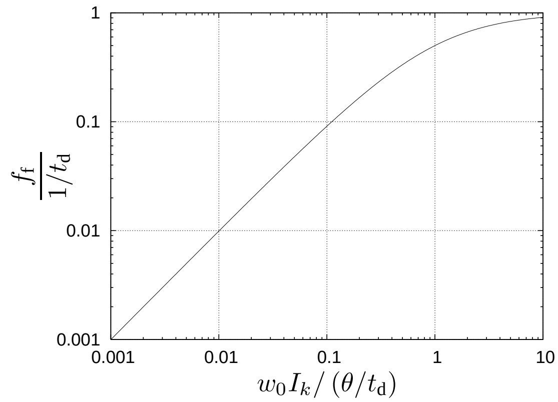

Figure 2: free-running spike frequency f_f of a non-leaky IAF neuron dependent on the continuous input $w_0 I_k$.

neighboring pixels in the same segment have similar grey levels. The corresponding neurons receive these grey levels as continuous inputs $w_0 I_k$ and $w_0 I_l$ respectively. A set of synaptic coupling weights $\{w_{\mu\nu}\}$ is introduced and establishes nearest neighbor coupling between them. Figure 3 summarizes the network structure.

In order to obtain synchroneity in a hypothetical segment, for each neuron in the segment it has to hold as an generalization of (9):

$$\theta = T_\mathrm{i} w_0 I_k + \sum_{l \in N_k} T_{\mathrm{p},l} w_{kl}, \tag{10}$$

where N_k is the set of neighbors making connections to neuron k, and $T_{\mathrm{p},l}$ is the part of the pulses from neuron l not overlapping with pulses from neuron k.

In order to establish (10) the weights have to be adjusted. This is accomplished by adapting them according to the states and membrane potentials of the connected neurons. Figure 4 shows state and membrane potentials of two neurons and motivates weight changes to obtain synchroneity. The general idea is to enhance the weight, if the receiving neuron is behind, to make it fire earlier in the next cycle; and respectively to attenuate the weight, if the receiving neuron is in advance. Two rules have been found on this base:

$$\text{rule 1:} \quad \dot{w}_{kl} = -\gamma w_{kl} + \begin{cases} \mu(a_k - \theta_k/2) & X_k = 0 \wedge X_l = 1 \\ 0 & \text{else} \end{cases} \tag{11}$$

$$\text{rule 2:} \quad \dot{w}_{kl} = -\gamma w_{kl} + \begin{cases} \mu(a_l - a_k) & \|a_l - a_k\| < \theta_a \wedge X_k = X_l = 0 \\ 0 & \text{else} \end{cases} \tag{12}$$

According to rule (11) a weight w_{kl} is adapted, when a pulse is transmitted over it ($X_l = 1$) and the post-synaptic neuron k receives that pulse ($X_k = 0$). If at this instant the membrane potential is closer to the threshold than to the reset potential, the weight will be

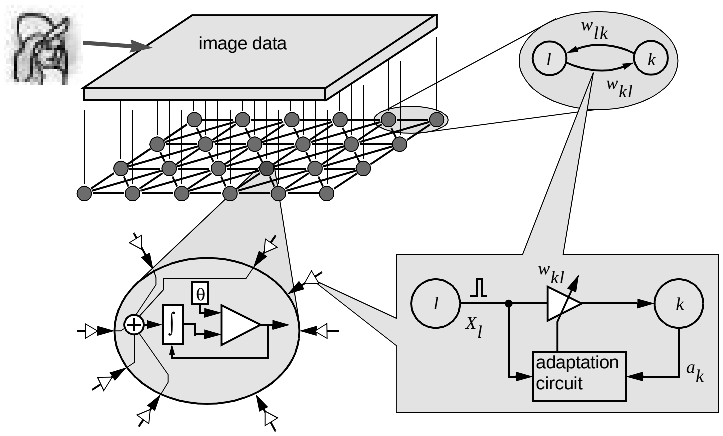

Figure 3: Structure of the neural network with adaptive weights.

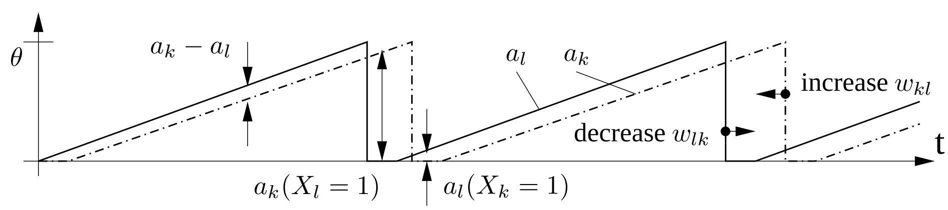

Figure 4: Membrane potential of two neurons and motivation for weight adaptation towards synchroneity. For details see text.

increased. If the membrane potential is closer to the reset potential, the weight will be decreased.

According to rule (12) the weight is adapted during the longer periods between pulses ($X_k = X_l = 0$). Here, the weight is adapted proportionally to the difference of the membrane potentials, if this difference is below a threshold θ_a.

At the border of hypothetical segments weights should decrease to small values, in order to not disturb synchronous activity within segments. At the boundaries continuous input $w_0 I_k$ has larger differences between neighboring neurons. Because of the different free-running frequencies the rightmost terms $+\mu(\ldots)$ of (11) and (12) will vary rapidly and indeterminately. The decay term $-\gamma w_{kl}$ provides weight reduction in that situation besides adding stability to the system.

As a result of the adaptation some weights can reach a stable periodic state, where the weight oscillates around a fixed non-zero value in the rhythm of the transmitted pulses. That is the case when

$$\int_0^{1/f_c} \dot{w_{kl}}\, dt = 0. \tag{13}$$

For rule (11) equation (13) reads as

$$\int_0^{1/f_c} \gamma w_{kl}\, dt = \int_{t_l^{(\nu)}}^{t_l^{(\nu)}+t_\mathrm{d}} \mu(a_k - \theta_k/2)\, dt. \tag{14}$$

From $\gamma w_{kl} > 0$ follows $\mu(a_k - \theta_k/2)\big|_{t_l^{(\nu)}} > 0$. During pulse transmission the post-synaptic membrane potential a_k is close to θ. Therefore, the pulse of the post-synaptic neuron ($X_k = 1$) follows shortly after the pulse of the pre-synaptic neuron ($X_l = 1$). The reciprocal weight w_{lk} between the neurons is quickly reduced to zero by $\mu(a_k - \theta_k/2) < 0$ and by the decay term $-\gamma w_{lk}$.

The by w_{kl} scaled pulse increases the membrane potential a_k of the post-synaptic neuron k. Therefore a stable periodic state can be reached, if the continuous input $w_0 I_k$ to the post-synaptic neuron k is less than that to the pre-synaptic neuron l.

For rule (12) equation (13) becomes

$$\int_0^{1/f_c} \gamma w_{kl}\, dt = \int_0^{1/f_c} dt \cdot \begin{cases} \mu(a_l - a_k) & \|a_l - a_k\| < \theta_a \wedge X_k = X_l = 0 \\ 0 & \text{else} \end{cases} \tag{15}$$

A stable periodic state can be reached, when the pre-synaptic membrane potential a_l is greater than the post-synaptic membrane potential a_k most of the time. Therefore the pre-synaptic neuron will reach the threshold earlier than the post-synaptic neuron. Again, the reciprocal weight w_{lk} between the neurons is quickly reduced to zero by $\mu(a_l - a_k) < 0$ and by the decay term $-\gamma w_{lk}$.

3.2 Activity Waves

Both rules lead to very similar pulse patterns. Lets consider a patch of the network, where the adaptation has led to synchronous activity. The weights connecting neighbors within this patch have been set to different values, such that the additional pulsed input to the neurons equalizes the difference in the continuous inputs. Then, for each neuron in the patch the following holds:

$$w_0 I_k \left(\frac{1}{f_c} - t_d \right) + \sum_{l \in N_k} w_{kl} T_{\mathrm{p},l} = \theta. \tag{16}$$

It follows that for different inputs $w_0 I_k$ the pulses of synchronous neurons cannot overlap completely, because $T_{\mathrm{p},l} > 0$ must hold in (16). Even if the neurons receive equal continuous inputs, non-overlapping activity must be conserved, once it has been established. If one of the neurons in the patch receives additional pulsed input, all others have to receive an equal amount to ensure the common pulse frequency.

As a consequence, in synchronous patches of the network the neural activity shows a wave-like patterns, which repeatedly run across the patch. Three different forms of waves have been observed so far in a large number of simulation experiments. They appear under

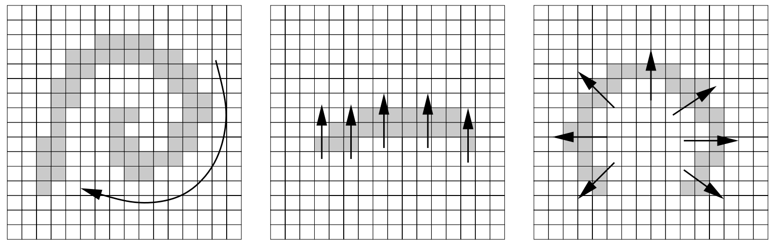

Figure 5: In synchronized patches of the network wave-like activity patterns can be observed. Three basic form occur in most of the simulation experiments: spiral forms which spin around a fixed central pixel, straight moving forms, and expanding circles or ovals.

various conditions in a wide range of the parameters of the adaptation rules. Figure 5 shows their basic shapes.

4 Implementation

We have implemented the PCNN in a massively parallel analog VLSI chip using an Infineon 130 nm CMOS technology. The chip comprises 128×128 neurons, each coupled to its 4 nearest neighbors by adaptive synapses capable of rules (11) and (12). The implemented neurons spike with frequencies of up to 10 kHz and require 10 to 30 pulses to achieve synchroneity. Images can be loaded into an analog frame memory with up to 100 frames per second, pulses are read out in real-time via an address event representation protocol. The chip occupies about 50 square Millimeters, figure 6 shows the layout of a spiking neuron with four adaptive synapses. The neural network dissipates about 5 Milliwatts, the input and output circuitry is expected to draw 100 Milliwatts from the supply of 1.5 Volts.

The analog implementation does not resemble the adaptation rules (11) and (12) exactly. Instead, the equations are roughly approximated and parameters haven been limited to practical values. Additionally, synapses and neurons are not perfectly identical among each other, as usual with analog implementations. Most parameters are reproduced with limited accuracy only. However, the implementation shows the same wave-like synchronization patterns. From the evaluation of extensive simulations accuracy levels have been determined, which ensure a good match between pulse patterns seen in the implementation and in simulations of the ideal network. Some technical details of the implementation and a discussion of the accuracy determination can be found in our previous papers [SRH$^+$02, SRH$^+$04].

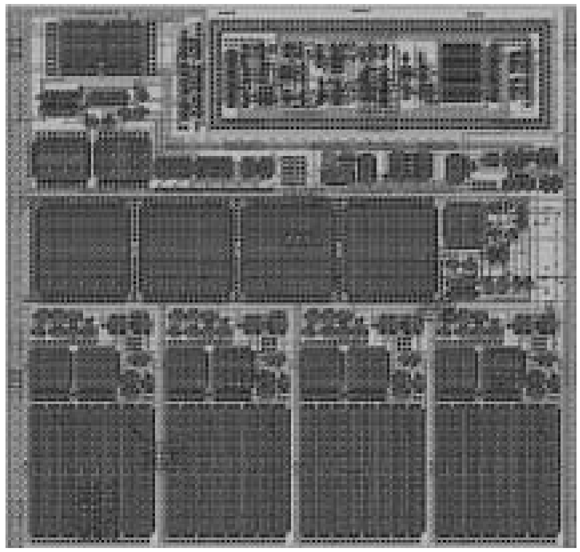

Figure 6: Layout of a neuron with four adaptive synapses

References

[BGSE01] Brecht, M., Goebel, R., Singer, W., und Engel, A. K.: Synchronization of visual responses in superior colliculus of awake cats. *Neuroreport*. 12:43–47. 2001.

[CBD+03] Chicca, E., Bandoni, D., Dante, V., D'Andreagiovanni, M., Salina, G., Carota, L., Fusi, S., und Giudice, P. D.: A VLSI recurrent network of integrate-and-fire neurons connected by plastic synapses with long-term memory. *IEEE Transactions on Neural Networks*. September 2003.

[In00] Indiveri: Modeling selective attention using a neuromorphic analog VLSI device. *Neural Computation*. 12:2857–2880. December 2000.

[RLS98] Roelfsema, P. R., Lamme, V. A., und Spekreijse, H.: Object-based attention in the primary visual cortex of the macaque monkey. *Nature*. 395:376–382. September 1998.

[SMJK98] Schoenauer, T., Mehrtash, N., Jahnke, A., und Klar, H.: MASPINN: novel concepts for a neuro-accelerator for spiking neural networks. *Workshop on Virtual Intelligence and Dynamic Neural Networks*. 1998.

[SRH+02] Schreiter, J., Ramacher, U., Heittmann, A., Matolin, D., und Schüffny, R.: Analog implementation for networks of integrate-and-fire neurons with adaptive local connectivity. In: *Neural Networks in Signal Processing NNSP'02*. Martigny, Switzerland. August 2002.

[SRH+04] Schreiter, J., Ramacher, U., Heittmann, A., Matolin, D., und Schüffny, R.: Cellular pulse coupled neural network with adaptive weights for image segmentation and its VLSI implementation. In: *Electronic Imaging 2004*. 2004.

[vdM81] von der Malsburg, C.: The correlation theory of brain function. Internal Report 81-2. Max-Planck-Institute for Biophysical Chemistry, Goettingen. 1981.